Reactive Localisation of an Odour Source by a Learning Mobile Robot*

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Abstract

The goal of this work was to enable a mobile robot to navigate autonomously towards a stationary odour source with the help of a sense of smell. Two electronic noses, each containing a set of gas sensors, mounted on top of a Koala mobile robot were used for detection of the odour. The sensing strategy used for data collection was investigated in order to reduce the influence of air turbulences on the sample handling process. Then a multi-layer artificial neural network was used to learn both the direction to the source and the required turning speed of the robot. An experimental validation was carried out to evaluate the performance of the complete system.

1 Introduction

Smell is perhaps the least studied sense in robotic applications. Electronic noses have been widely used under laboratory conditions, e.g., for food analysis, but so far there have been few applications on mobile platforms in real world environments, due to the complexity of the sample handling process and environmental influences such as air turbulence.

The aim of this work was to develop an odour localisation system that enables a mobile robot equipped with metal oxide gas sensors to navigate autonomously towards a specific odour source. Future applications of this technology would include detection of gas leaks, inspection of pipes in factories, and mine-sweeping to mention but a few.

The state-of-the-art in smelling mobile robots consists of experiments conducted in environments with a strong constant airflow (see Related Work). The next step towards navigation in environments without a carefully controlled airflow presents a seriously non-trivial challenge for current research. In many cases, the response of the gas sensors becomes dominated by air turbulence rather than concentration differences [11]. Additionally, the signals obtained from metal oxide gas sensors vary non-linearly with respect to gas concentration and have a slow response to changes in concentration. This makes the interaction between sensors and environment very difficult to model.

This last point is illustrated by the results presented in Fig. 1. In this experiment, two of the gas sensors on the stationary mobile robot were exposed firstly to clean air, then after 2 minutes a jar of acetone was opened in the vicinity of the robot. The gradual response of the sensors to the increased gas concentration can be seen, until the acetone was removed after 5 minutes. It can be seen that a further 3 minutes was required before the sensor values returned (approximately) to their initial reference values.

In the rest of this paper, we present a complete system for reactive localisation of an odour source in indoor office environments with only partially controlled airflows. Firstly, we designed an improved hardware set-up for odour sensing on a mobile robot (the Örebro Mark II mobile nose, see Section 3). Then we conducted experiments to determine an appropriate sensing strategy (Section 4), and developed a software controller based on an artificial neural network to learn the odour localisation task by associating sensor patterns with the appropriate motor responses (Section 5). Finally, we conducted a series of experiments to validate the performance of the complete system (Section 6), which is followed by conclusions and suggestions for future work (Section 7).

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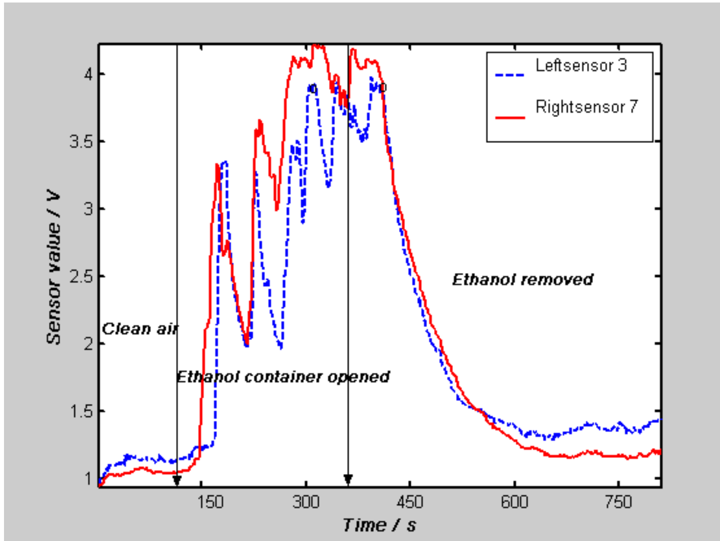


Figure 1: Response of two TGS-822 sensors to the introduction (2 minutes) and removal (5 minutes) of a beaker of acetone. Irregularities in the gas concentration due to air turbulence can also be seen.

2 Related Work

Early work on learning robots included Braitenberg's famous thought experiments with synthetic "vehicles" [3]. Fig. 2 shows two of these vehicles in which the sensors were directly connected to the actuators by means of an imaginary wire such that the force exerted by the motors is proportional to the quantity measured by the corresponding sensor. Braitenberg vehicles have been implemented on real mobile robots using single-layer feedforward neural networks, where the "wires" have modifiable connection strengths that are tuned by the neural network training algorithm [12].

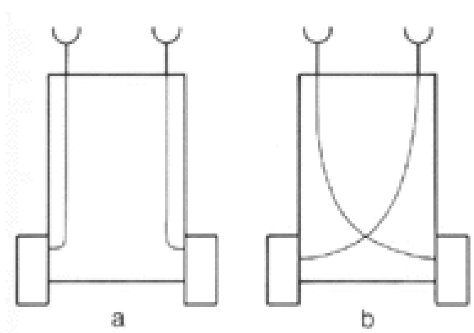


Figure 2: Examples of Braitenberg vehicles.

Unfortunately for the current generation of smelling robots, it is not possible to implement a Braitenberg-type vehicle directly due to the air turbulence, delayed response and non-linear properties of the gas sensors, as illustrated in Fig. 1. Instead, we have found a multi-layer feedforward neural network to be a suitable mechanism for learning the odour source localisation task.

Several studies that integrate odour sensors and mobile robots have appeared in the literature. Most of these studies address one of two problems: following an odour trail on the ground [18, 17, 16]; or localisation of a distant odour source. In this paper, we focus on the latter problem.

Early systems for odour source localisation were based on the idea of following the gradient of the gas concentration [15]. To deal with the problem of air turbulence, other systems have used a combination of gas sensors and anemometers [9], or have introduced forced ventilation [6]. To compensate for the delays in the sensor response, later systems have incorporated a dynamic model of the sensor response. Ishida and colleagues developed a model-based "odour compass" [7] which can measure the bearing to an odour source with good speed and accuracy in a closed environment if the airflow is constant with respect to time (typically around $0.3m/s$). The parameters of the model were obtained by a recursive least squares method. In another work [8], a dynamic model of the sensor plus a model of the gas distribution was

Model	Typical substances detected
TGS822	alcohol, toluene, xylene, etc.
TGS826	ammonia
TGS880	gases in cooking process
TGS882	alcohol vapour

Figure 3: Top: Figaro gas sensors. Bottom: Sensors used and their selectivity characteristics.

used to estimate the distance to the odour source.

While the above techniques have produced good results, the reliance on a known dynamic model of the sensor response may reduce their applicability. Parameter identification is a difficult and time consuming procedure; the learning approach presented in this paper offers an attractive alternative. The reliance on a constant airflow imposes a severe restriction on the range of possible applications. Gas distributions are also notoriously difficult to model without carefully controlled environmental conditions.

Lilienthal and colleagues [11, 10] investigated the use of gas sensors on mobile robots in uncontrolled environments, without assuming a constant airflow. Under these conditions, even small air movements that are indiscernible to the human observer can make it very difficult to detect spatial and temporal differences in odour molecule concentration [13]. In [11], it was found that odour concentration measurements taken in a vacant apartment by a robot driving at a constant speed of $15cm/s$ were subject to strikingly lower levels of turbulence than those collected with a stop-sense-go strategy. One explanation for this result is that the constant speed of the robot adds an extra airflow relative to the gas sensors [11]; another is that the deceleration of the stopping vehicle itself causes extra turbulences which affect the sensor readings. In this paper, we confirm this result in the experiments presented in Section 5.

Finally, in our previous work [4] we introduced a system for learning the direction to a stationary odour source using the Örebro Mark I mobile nose. In this system, both the odour source and robot were kept at a stationary position, and the robot attempted to localise the source only by turning itself. The sequence of recorded sensor signals was fed into a recurrent artificial neural network, which was trained to predict the correct angle towards the source. The work presented here is a natural extension of our previous work; after first locating the approximate direction of the source by merely turning, the robot can then drive forwards using its twin electronic noses to steer itself reactively towards the source.

3 Experimental Set-up

A Koala mobile robot with 6 wheels and 16 infrared sensors was used for all experiments. The infrared sensors were used to detect obstacles and to prevent the robot from driving over the odour source. In this work, the robot simply stopped when an obstacle was found: this would either be the odour source in the case of a successful trial, or another object such as a wall in the case of an unsuccessful trial.

Figaro solid-state gas sensors were used for the construction of the electronic noses. These sensors have a limited sensitivity to various substances. Four sensors of varying selectivity, as indicated in Fig. 3, were used to construct the sensor array mounted on each side of the vehicle (the same four sensor types were used in both cases).

Acetone and ethanol were used to provide the odour source, because these substances are volatile, strong smelling and easily detected. All of the sensors in Fig. 3 are sensitive to these substances; the primary motivation for using 4 different sensor types was to increase the robustness (noise tolerance) of the odour detection system by using multiple, partly-redundant sensors.

The environment used for the training of the system was an empty room at Örebro University with a ventilation control system. The airflow in the room was a major concern in our experiments due to its effect on the propagation of gases. In order to collect usable sensor data for training the system, we found in was necessary to introduce some structure into the room. A circular area with artificial walls was therefore constructed in the middle of the room, as shown in Fig. 4. However, in the validation experiments presented in Section 6 we removed the artificial walls and also tested the system in a different room. Humidity was an uncontrolled influence in our experiments.

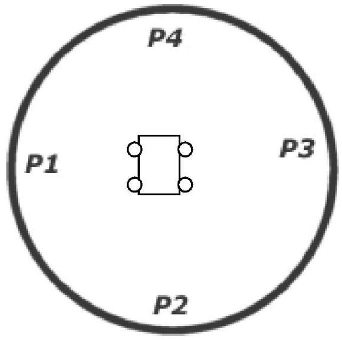


Figure 4: Schematic diagram of the circular area used for training of the system, with an approximate diameter of $3.5m$. P1, P2, P3 and P4 are the various positions of the odour source during collection of sensor data for training and testing.

The software development environment chosen for this work was Matlab, because it contains a useful software library for artificial neural networks and allows for a very simple serial port connection to the Koala robot and the gas sensors in the electronic noses. One potential disadvantage of Matlab for real-time applications is its slow processing speed, but this was not found to be a problem in any of the experiments reported here.

4 Nose Hardware Design

The electronic noses used in this work were based on the original design of a stand-alone sensor at AASS consisting of a tube containing 8 Figaro gas sensors and a suction fan for maintaining a weak constant airflow through the tube [1]. This sensor was later mounted on the Koala mobile robot, and the tube was divided into two chambers or "nostrils" to create the Mark I mobile nose [4], as shown in Fig. 5.

In the previous work, the mobile robot attempted to find the direction of the odour source only by turning itself, without moving forwards. In order to achieve the second part of the localisation task of driving forwards and steering towards the odour source, we found it was necessary to modify further the design of the system.

An experiment was first conducted with the Mark I mobile nose, where data from the gas sensors was collected while the robot was driving forward firstly with the odour source to the right of the robot and secondly with the source to the left of the robot. The results in Fig. 4 show the data collected for 2 sensors of the same type, one mounted in each chamber of the nose. The data from the 2 sensors was not clearly separated, due to the close proximity of the two chambers in the nose, indicating a fault in the design for this particular task.

Instead, we found that the design of the nose could be improved by using two separate tubes, each containing 4 similar sensors, mounted on either side of the robot, as shown in Fig. 5. With this Mark II

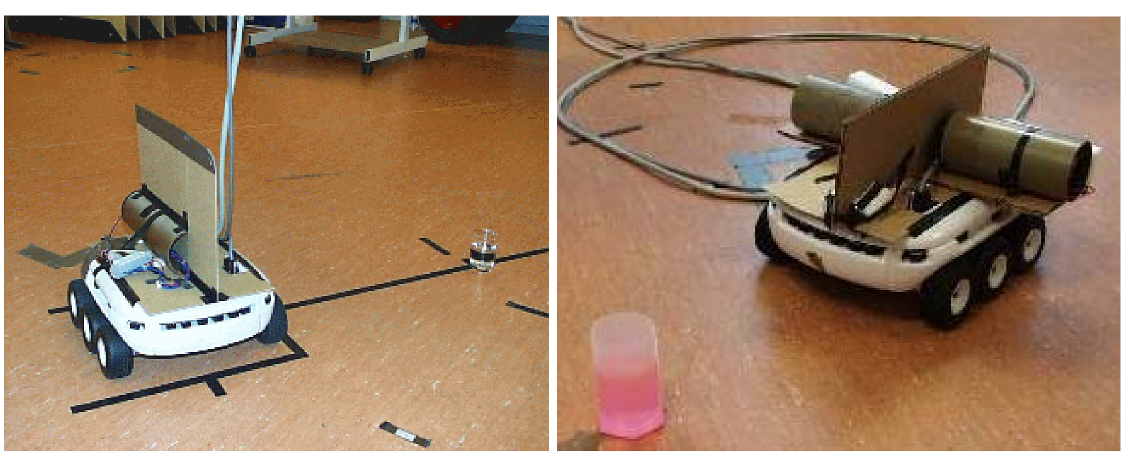


Figure 5: Left: the Örebro Mark I mobile nose. Right: the Örebro Mark II mobile nose.

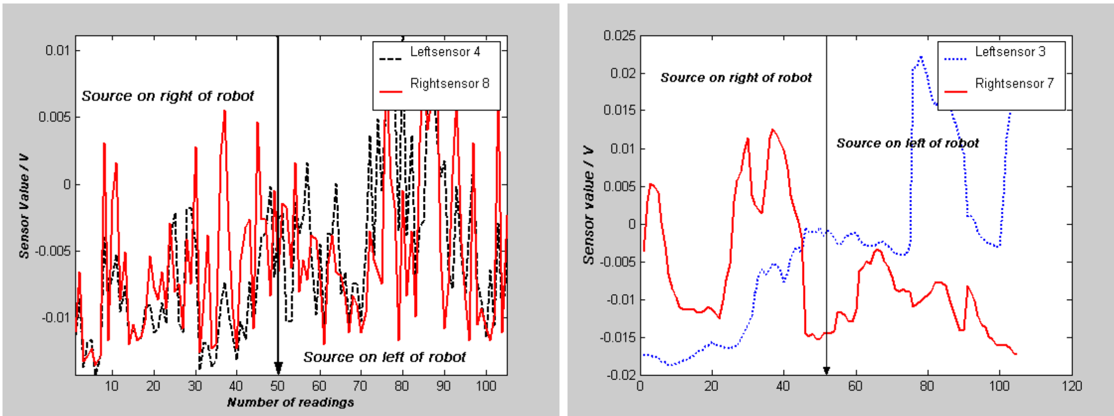


Figure 6: Left: data collected with the Mark I. Right: data collected with the Mark II.

mobile nose, we were able to achieve a much better separation of the sensor data from the two sides of the vehicle, as shown in Fig. 6. We also observed that the relative response of the sensors on the left and right sides of the vehicles depends roughly on the distance and direction to the odour source, indicating that this design was a good candidate for solving the odour source localisation task.

5 Sensing Strategy

The strategy that is used for collecting the sensor data plays a very important role in the detection and localisation of an odour source. The results obtained with two different strategies are discussed as follows.

First, we used a stop-sense-go strategy. Here the robot was programmed to drive straight forwards, stopping every $5cm$ to take one set of sensor readings. The odour source was placed at a distance of $80cm$ directly in front of the starting position of the robot.

Second, we used a constant forward driving speed, without stopping to take the sensor readings, with the same initial conditions as with the previous strategy.

The results in Fig. 7 show the response of one of the TGS822 sensors for the two strategies. These results show very clearly the superiority of the second sensing strategy, also confirming the same result as reported earlier by [11]. It seems that the motion of the mobile robot has a fundamental role in the propagation of gases around the sensors, and consequently has a great effect on the turbulences affecting the sensor responses.

6 Artificial Neural Network

Due to the noise, delay and non-linearity of the sensor signals, it is very difficult to solve the odour source localisation problem analytically. Instead, an artificial neural network (ANN) was found to be an attractive alternative for solving this problem. We used a multi-layer feedforward (MLFF) network with an input layer consisting of 8 units corresponding to the 8 gas sensors mounted on the robot, one

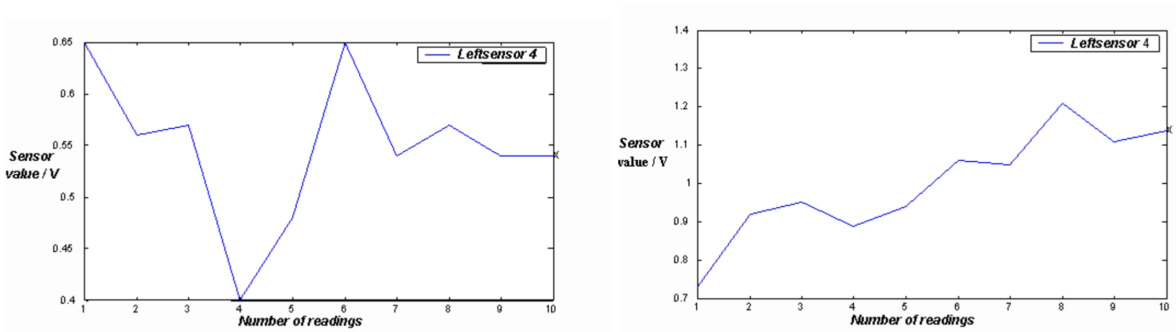
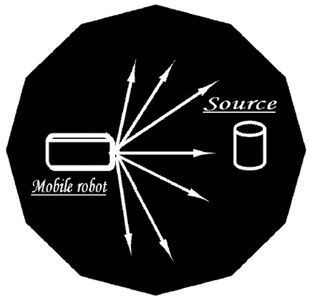


Figure 7: Left: Data collected with a stop-sense-go strategy. Right: Data collected with a constant forward speed.



Angle to Source	Target Output of ANN
85°	1.0
55°	0.67
25°	0.33
0°	0
-25°	-0.33
-55°	-0.67
-85°	-1.0

Figure 8: Top: collection of sensor data for training and testing at seven different angles to the source. In each run the robot drove straight forward and collected 30 sets of data. Bottom: coding of the seven angles for training the artificial neural network.

hidden layer of 4 units, and one output layer of 1 unit to solve this task. The number of hidden units was determined by minimising the sum squared error on an independent test data set, using the standard back-propagation algorithm for training [2].

The MLFF network was trained and tested using sensor data collected in the environment of Fig. 4. The odour source, a beaker with an opening of $7cm$ in diameter, was filled with ethanol and placed at a distance of $80cm$ from the robot at four different positions shown in Fig. 4. In order to learn the direction to the odour source, data was collected with the robot driving in 7 different directions as shown in Fig. 8. A total of 630 sets of sensor data were collected. 75% of the collected data was used for training the network, and the remaining 25% was used for testing. The coding of the desired output for the single output motor neuron was determined as in Fig. 8. The sign of the output determines the turning direction of the robot towards the source, and the magnitude of the output determines the turning speed. The performance of the trained network on an independent test data set is indicated in Fig. 9.

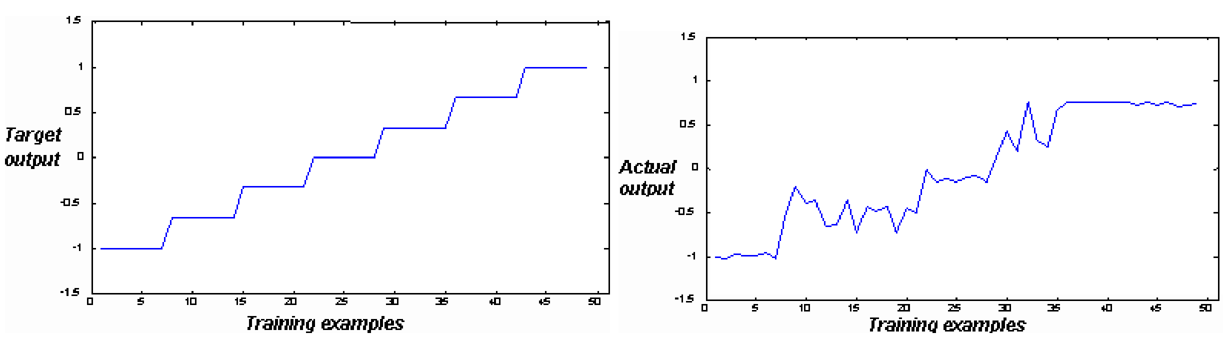


Figure 9: Left: desired output for the MLFF network on the test data. Right: actual output of the MLFF network on the test data.

7 Experimental Validation

In order to validate the performance of the complete system, we conducted five separate sets of experiments which are detailed as follows. In these experiments, we assumed that the robot would start with a very rough initial estimate of the angle to the source (using the odour orientation system described in

[4]), so we used starting angles between -90 and +90 degrees to the source.

7.1 Familiar environmental conditions

This experiment was undertaken in conditions which were the same as those used during development and training of the system. That is, the odour source was placed in the same positions P1-P4 as before in the environment of Fig. 4. Results of ten runs are given in the following table.

Run	Dist. to source/cm	Starting angle/deg	Localisation error/cm	Reference dist./cm
1	70	85	17	95
2	70	85	0	95
3	70	-85	0	95
4	100	-85	22	135
5	100	0	100	0
6	100	0	27	0
7	100	0	225	0
8	150	85	25	202
9	150	-85	10	202
10	150	0	0	0

The final position of the robot from the source (stopping using the infrared sensors to detect the source) is indicated as the localisation error in cm. The reference distance is the expected localisation error if the robot were to simply travel in a straight line without trying to steer itself towards the source.

In this experiment, the robot found the source in 8 runs out of 10 (the failures were on runs 5 and 7; we counted a failure as any localisation error of 50 cm or more). We observed that failures happened when the robot began facing towards the source at 0 degrees. This indicates a design fault in the Mark II mobile nose; the sensors are mounted at the sides of the robot, so the system is very good at locating the source when it is at one of the two sides, but there is insufficient sensing capacity at the front of the vehicle. A better design is therefore still required (see suggestions for Future Work).

7.2 Partly-familiar environmental conditions

In this experiment, the same environment was used but the odour source was placed at different positions which were not used during training of the system.

Run	Dist. to source/cm	Starting angle/deg	Localisation error/cm	Reference dist./cm
1	80	85	50	108
2	60	85	40	81
3	60	90	0	85
4	80	0	100	0
5	80	0	45	0
6	80	-90	130	113
7	60	-80	25	77
8	60	90	15	85
9	80	90	0	113
10	150	0	150	0

The robot found the source in 6 runs out of 10. Again, the same design fault at zero starting angles was observed. Higher localisation errors were generally observed at greater starting distances from the source.

7.3 Multi-substance localisation

Our intention in this experiment was to the test the ability of the system in a multi-substance localisation problem. Two different sources (ethanol and acetone) were placed at different positions as indicated in Fig. 10. Recall that the system had been trained only with ethanol as the odour source.

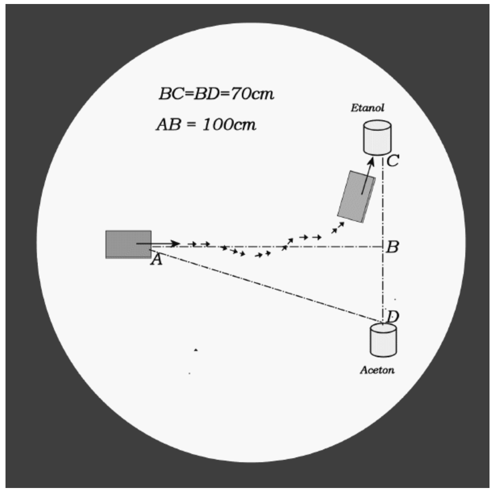


Figure 10: Experiment with two different odour sources.

Run	Dist. to source/cm	Starting angle/deg	Locn. err./cm	Ref. dist./cm	Source found
1	100	35	0	70	Eth.
2	100	35	40	70	Ace.
3	100	35	20	70	Ace.
4	100	35	20	70	Ace.
5	80	41	30	70	Eth.

The system was able to find one of the two sources in each run, but was unable to distinguish between ethanol and acetone. This was not really surprising as the system had only been trained with ethanol, and the two substances produce very similar sensor responses anyway.

7.4 Unfamiliar environmental conditions

In this experiment, the artificial walls in the environment of Fig. 4 were removed and the odour source was also placed at a position not experienced during training. Encouragingly, the robot was successful in all trials.

Run	Dist. to source/cm	Starting angle/deg	Localisation error/cm	Reference dist./cm
1	70	90	0	99
2	70	-90	0	99
3	100	0	20	0
4	100	-90	30	141
5	80	0	45	0

7.5 Completely new environment

Here, we moved the mobile nose to a different room with no artificial walls. Different distances and starting angles were tested. The results were very good, successful in 9 out of 10 trials.

Run	Dist. to source/cm	Starting angle/deg	Localisation error/cm	Reference dist./cm
1	60	-80	0	0
2	80	-80	10	0
3	80	80	10	20
4	60	80	0	10
5	65	-85	0	0
6	90	85	0	0
7	100	0	15	0
8	100	0	10	0
9	100	-80	60	30
10	100	80	20	15

7.6 Statistical Analysis

To evaluate the significance of the results, we used Student's t-test for paired samples [14]. Here, we tested the null hypothesis that these results were obtained by chance, comparing the actual localisation errors obtained by the mobile nose to the reference distances (i.e., the expected localisation errors of a non-smelling robot). Due to the design fault discussed above, the difference in performance between the two systems was not found to be significant when zero starting angles were included in the analysis. However, when we excluded the runs with zero starting angles from the analysis (11 runs discarded out of 40), the difference was extremely statistically significant ($P < 0.0001$). The data used for the test is summarised as follows.

Group	**Localisation Error**	**Reference dist.**
Mean	19.79	103.55
S.D.	26.98	34.36
S.E.M.	5.01	6.38
N	29	29

8 Summary of Results

The main findings of our experimental work can be summarised as follows:

- The performance of the system is roughly inversely proportional to the starting distance of the robot from the odour source.
- The trained system is not bound to a specific position or environment: the robot managed to find the source in an unknown environment.
- The performance of the system is at its worst when the robot starts facing directly towards the source at zero degrees, indicating a design fault in the Mark II mobile nose as discussed above.
- The generalisation performance of the trained neural network was very good.

9 Conclusions and Future Work

In this paper, we have developed a new sensing system for odour source localisation with a mobile robot. A new design of the mobile nose was established, including an improved sensing strategy. An experimental validation was performed, demonstrating a reactive navigation system for following an odour gradient.

The results indicate that the three main system components, namely the hardware design, sensing strategy and learning software controller, depend heavily on one another and cannot be studied in isolation. Further work will include improvements to the design of the mobile nose, possibly including more sensors around the front of the vehicle to improve the sensor coverage. One option would be to combine the sensing capabilities of the Mark I and II platforms (Fig. 5).

An important aspect that we explored in our previous work was the role of internal state in determining the location of the source [4]. In that work on finding the initial orientation towards the source, we found that a simple recurrent network (SRN) [5] produced better performance than the MLFF network used here because it incorporates feedback connections which allow the network to encode history information about previous input vectors. While the previous system was constrained to a single degree of freedom, only being able to turn at a fixed position, this mechanism might also be very useful here for several reasons. First, the recurrent connections would allow integration of measurements over time, enabling either temporal averaging or temporal differencing [17]. Second, the propagation of odours is not instantaneous, so a recurrent network might be able to capture information about concentration changes where the sensors on the side of the vehicle furthest from the source respond later than those nearest to the source.

Future work will also investigate other machine learning algorithms. We will also investigate other navigation strategies, possibly including environment modelling (e.g., map building) and robotic implementations of strategies used by biological systems such as insects.

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